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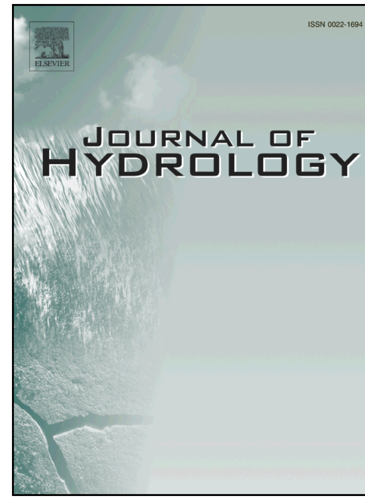

Research papers

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Attributing variations of temporal and spatial groundwater recharge: a statistical analysis of climatic and non-climatic factors

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Abstract

This paper demonstrated the benefits of statistical methods when investigating the climatic and non-climatic drivers responsible for variations in groundwater recharge with a series of up to 43 years of annual recharge for 426 bores in South-East South Australia. We identified the factors influencing groundwater recharge based on 71 climatic metrics and 13 non-climatic metrics (including groundwater abstraction). The results showed: 1) Rainfall during April to October was the most important variable influencing recharge temporal variation, with its decline identified as the most significant factor related to recharge reduction; 2) In contrast, a negative correlation between rainfall during December to February (DJF) and annual groundwater recharge was found. This suggests that a seasonal shift in rainfall (such as decreasing rainfall during April to October and an increase during DJF) can result in a decline in recharge even when the annual rainfall remains unchanged; 3) The length of wet spells (consecutive rain days) and increasing PET were additional significant predictors for recharge temporal variation. It demonstrated that a simple empirical relationship (such as recharge as a fixed percentage of rainfall) is not a reliable estimation of renewable groundwater resources under changing climatic conditions; 4) There is a statistically significant spatial correlation between mean groundwater depth and recharge, and this implies that a reduction in rainfall can lead to a positive feedback loop of declining recharge and water level; 5) Spatially the most statistically significant factors influencing groundwater recharge were soil types and land attributes. The findings of this study can identify which stressors should be included when investigating the impact of climate change on groundwater recharge.

Keywords

Groundwater recharge, climate changes, statistical analysis, temporal and spatial variations, Australia

1. Introduction

Groundwater, the largest distributed store of fresh water in the world, plays a very important role in sustaining ecosystems and enabling human adaptation to climate variability and change (Taylor et al., 2013). Therefore, accurate assessment of groundwater resources, and particularly renewable groundwater resources, is critical to support a resilient and sustainable economy of the future. Accordingly there are numerous studies in the literature that investigate the impacts of climate change and variability on groundwater (Table 1). These studies can be categorized into three groups: Group 1 studies (1-5 in Table 1) are review papers; Group 2 studies (6–11 in Table 1) build the relationship between groundwater recharge/groundwater level and climate statistics based on historical observations; Group 3 studies (12–23 in Table 1) involve using a groundwater/hydrological/eco-hydrological/water-balance model and future climate projections from General Circulation Models or Global Climate Model (GCMs) to investigate the impacts of climate change and variability on groundwater.

The main challenges for the third group of studies are the large uncertainties from the choice of GCMs and associated downscaling methods from GCMs, as well as ensuring that the future relationship between groundwater recharge/level and climate variables are physical explainable. The second group of historical linkage between climate variables and groundwater recharge/level could be used as a benchmark for the climate change impact studies of group three. For example, the statistical analysis indicated that the same annual rainfall with a seasonal shift could result in a decline of recharge, which can serves as a benchmark to test whether a groundwater model study from group three could simulate this relationship under climate change scenario. However, limited climate variables are used in existing studies.

Therefore, the objectives of this study are to extend the approach or methodology used by studies in the second group to explore the relationship between a previously developed groundwater recharge dataset and a wide range of climate statistics (38 rainfall, 12 temperature and 21 evaporation) and non-climate variables (10 land and soil attributes, groundwater extraction, NDVI, and groundwater depth). This could identify the controlling factors of temporal and spatial groundwater recharge variability. The results are not only useful for regional groundwater management, but also serve as a reference for studies of climate change and variability impacts on groundwater.

2. Dataset and Methods

2.1. Study region

The southeast corner of South Australia (Fig. 1) has been selected as a case study because it has: 1) considerable recharge to the groundwater system, which is the only source of water in the region (Harrington and Lamontagne, 2013); 2) limited surface runoff (Leaney and Herczeg, 1995); 3) a long history of field investigations for groundwater recharge, and a dataset of groundwater recharge is available (Section 2.2 provides detail information about this dataset) (Crosbie et al., 2015).

The climate of this region is water-limited Mediterranean, with hot dry summers and cool wet winters (Jones et al., 2009). The long-term (1970–2012) mean annual rainfall is 625 mm with a north-south gradient ranging from 456 to 850mm. The mean annual temperature is 14.5ºC with a range of 13.6 – 15.2ºC. The annual mean of class-A pan evaporation averages 1400 mm with a south-north gradient ranging from 1260 to 1550 mm. The FAO56 potential evapotranspiration (Allen and Food and Agriculture Organization of the United Nations., 1998) averages 1040mm with a range of 900 to 1060 mm.

The region is defined by the extent of the tertiary Gambier Basin in South Australia. Land use in this area is dominated by livestock production, dryland and irrigated crop production and plantation forestry (Harrington and Lamontagne, 2013). Irrigation supplies are derived almost entirely from groundwater and are used for cropping and some pastoral use. Irrigation is used intensively in viticultural areas concentrated along the Naracoorte Range and its western footslopes (Harrington and Lamontagne, 2013)

2.2. Groundwater recharge dataset

The time series of annual groundwater recharge produced by Crosbie et al. (2015) was used in this study. The selected data were estimated from monthly or semi-annual field measurements with the water-table fluctuation (WTF) method, which is a simplification of complex phenomena controlling movement of water to and from the water table (Healy and Cook, 2002). Because of its simplicity, as well as wide availability of observed water-levels, the WTF method has been used for a very long time in the literature (Meinzer, 1923) and has been comprehensively reviewed by Healy and Cook (2002). Recharge is calculated using the WTF method as:

$$R = S_y \frac{\Delta h}{\Delta t} \quad (1)$$

where R is recharge, S_y is the specific yield, Δh is the change in the groundwater level over a specified period of time (Δt).

Although the WTF method has some drawbacks, such as the specific yield is assumed to be known and constant over the calculated time period (detail discussion in Section 3.5.1), it is still amongst the most widely used methods currently available (Crosbie et al., 2010). In addition, Healy and Cook (2002) suggested WTF was best applied to areas with relatively shallow water tables, which is suitable for our study region.

The dataset of recharge used here is fully described in Crosbie and Davies (2013) and has also been used in Crosbie et al. (2015) and Doble and Crosbie (2017). The method used is identical to that of Brown et al. (2006) whose recharge estimates have been accepted by the local community and adopted for use in the water allocation plan for the region (SENRMB, 2013).

The recharge estimates used in this paper have been shown to be comparable to estimates made using the chloride mass balance and a water balance using remotely sensed actual evapotranspiration (Crosbie et al., 2015) in areas where the assumptions behind the methods make a comparison a sensible thing to do.

The original dataset has recharge data from 465 groundwater bores, but only 426 bores located in the state of South Australia were used in this study (the other 39 in Victoria were excluded here). Fig 1 shows the spatial distribution of these 426 boreholes. The length of groundwater recharge time series varies from 3 to 41 years with mean and median values of 21.6 and 21.5 years, respectively. Notably the bores with relative longer records (e.g. longer than 25years) are evenly distributed across the study region. It indicates that the dataset is appropriate for regional-average study and effects of the bores with relative shorter records (e.g. shorter than 25 years) are limited.

2.3. Climate datasets

The SILO Data Drill data (Jeffrey et al., 2001), which provides 0.05° gridded daily climate variables across Australia, were used in this study. The dataset is interpolated from station measurements made by the Bureau of Meteorology (BoM). The interpolations are based on the smoothing splining and kriging techniques described in Jeffrey et al. (2001). The data in the Data Drill are all synthetic; there are no original meteorological station data in the calculated grid fields.

Two sets of climate parameters were used in this study: one is rainfall statistics and another is atmospheric demand variables, such as temperature and evaporation (Table 2). For rainfall, 38 statistics (Table 2) were calculated from daily data. These statistics are potential factors that affect recharge. They include annual rainfall, seasonal rainfall, extreme rainfall (daily maximum rainfall, 99th and 95th daily rainfall), rainfall days, rainfall intensity, and wet/dry spell-length. There are two reasons to include seasonal rainfalls from May to September and from April to October: a) This period is the rainfall season and accordingly the accumulated rainfall from May to September and from April to October occupy about 62% and 77%, respectively, of annual rainfall; b) The water table usually is the deepest in April/May and shallowest in September/October.

2.4. Non-climate datasets

Three types of non-climate datasets (Table 2) which have potential impacts on recharge were used in this study:

Land and soil attribute datasets. For a given climatology, land and soil attributes are additional major factors that affect spatial variation of recharge. Ten groups of land and soil datasets are used in this study (Table 2). The detailed descriptions of these datasets can be found at https://data.sa.gov.au/data/dataset.

Groundwater extraction dataset. The groundwater extraction dataset for the Southeast of South Australia, 1970–2013, developed by Harrington and Li (2015), is used in this study. The basis for this dataset is a metered groundwater extraction dataset for 2009–2013. The historical groundwater extraction is estimated assuming that the average annual groundwater extraction rate for an individual bore is constant over time. Therefore, it cannot be used at an individual bore scale. Instead, it is used at the regional scale, because the number of active bores varies over time.

The normalized difference vegetation index (NDVI). A scalar indicator that can be used to simply and quickly identify vegetated areas and their "condition", the most commonly used index to detect live green plant canopies in multispectral remote sensing data. The NDVI dataset used in this study was extracted from BoM website (http://www.bom.gov.au/jsp/awap/ndvi/index.jsp). This satellite data comes from the Advanced Very High Resolution Radiometer (AVHRR) instruments on board the National Oceanic and Atmospheric Administration (NOAA) series of satellites, which are operated by the US (http://noaasis.noaa.gov/NOAASIS/ml/avhrr.html). It was available from April 1992 to present and has three missing months in 1994/1995.

2.5. Statistical methods

2.5.1 Correlation coefficient and simple linear regression

The Pearson's correlation coefficient (r) and least-squares linear regression are used to explore possible relationships between annual groundwater recharge as estimated by WTF method and climate and non-climate variables. Least-squares linear regression is a statistical technique to understand the association between one independent variable (such as climate and non-climate variables in this study) and one continuous dependent variable (such as groundwater recharge). The significant level α=0.05 (which corresponds a $p < 0.025$ with a two-sided test) is used in this study to detect whether a correlation coefficient is statistically significant.

2.5.2 Stepwise regression

Stepwise regression is a technique of fitting regression models sequentially. In each step, an explanatory variable is added (forward stepwise) or removed (backward stepwise) based on some statistical criterion. The forward stepwise regression starts with no variables in the regression model, investigates the addition of each potential variable using a chosen statistical criterion, and then adds the variable whose inclusion gives the most statistically significant improvement of the regression model. This process continues to run until no improvements can be achieved with the potential variables. In contrast, backward stepwise regression starts with a model to include all potential variables, investigates the removal of each variable within the model by a statistical criterion, and then removes the variable whose loss gives the most statistically insignificant deterioration of the regression model.

The *step* function from R (https://www.r-project.org/) was used in this study for the stepwise regression. The default Akaike Information Criterion (AIC) estimator is used as the criterion to stop the stepwise regression for both forward and backward models.

Stepwise regression is a simple and fast method to explore large amounts of potential predictors and to select the best predictor variable combinations from the available variables. However, it does have disadvantages, which include but are not limited to: 1) after a predictor is selected (forward) or removed (backward), it will be kept/deleted from the final model; and 2) if two predictor variables are both highly correlated, only one may make it into the final model. These disadvantages mean the final model may include trivial predictors or exclude important variables.

2.5.3 Best models from all combinations

The best models from all combination method (Miller, 2002) is a complementary technique to select important predictors for a regression model, i.e., to search the important climate and non-climate variables affecting groundwater recharge. For example, in order to find the two most important factors for groundwater recharge, all combination of two potential variables are used to build a regression model. The two predictors for the best fit model are then assumed to be the two most important variables and these two predictors may or may not include the best single predictor variable. We can also choose the best 5 or 10 models to explore which variables are the most often chosen, because in some cases the difference between the best two fitted models are very small and variables are quite different.

The R-package *leaps* is used in this study to investigate the important factors for groundwater recharge by performing an exhaustive search for the best subsets of the climate and non-climate variables. It uses an efficient branch-and-bound algorithm (https://cran.r-project.org/web/packages/leaps/leaps.pdf).

2.5.4 Relative importance

After the important climate and non-climate variables are selected based on stepwise regression and best models from all combinations, the relative importance method can be used to quantify the contributions of each individual predictor to the multiple regression model. Each predictor's contribution is the r^2 from univariate regression, and all univariate r^2-value add up to 100%. The relative importance used in this study is based on the approach proposed by Lindeman et al. (1980) and recommended by Gromping (2006) with his R-package *relaimpo.*

3 Results and Discussion

3.1. Correlation coefficient between groundwater recharge and climate variables at each bore

3.1.1. Rainfall statistics

The correlation coefficients between groundwater recharge and 38 rainfall statistics across 310 bores with a length of 15 years or more (Fig. 2) shows that rainfall is the most important factor for recharge, but some rainfall statistics are more significant than others.

In term of annual/seasonal rainfall, total rainfalls from May to September and April to October have an overall higher correlation coefficients than annual rainfall (Fig. 2). It implies that these seasonal rainfalls are more important than annual rainfall for groundwater recharge. It is physically explainable because: a) this period is the rainfall season and b) the water table usually is the deepest in April/May and shallowest in September/October. Annual total rainfall and June-July-August (JJA) rainfall also have a high correlation coefficient with recharge. In contrast, December-January-February (DJF) seasonal has a negative, but weaker, correlation with groundwater recharge. There are at least two possible underlying physical mechanisms for this phenomena: a) DJF rainfall usually cannot reach the groundwater level due to its low amount. But an increasing DJF rainfall could potentially make part of its rainfall reach groundwater level. It makes the annual deepest water table a little shallower, and accordingly results in a decrease in estimated recharge: b) An increasing DJF rainfall could lead to increased plant growth and consequently higher actual evaporation, which then results in less recharge. The detail physical processes of DJF rainfall and groundwater recharge is beyond the scope of this study, but the opposite signs of correlation with recharge in JJA and DJF could indicate that a simple seasonal shift of annual rainfall could lead to a decline in recharge, even if the annual rainfall remains the unchanged. It reinforces the caveats of many studies in the literature regarding water management and planning under a future climate where recharge is estimated using simple empirical relations, e.g. percentage of rainfall or the Maxey-Eakin method (NSW Department of Primary Industries, 2015; Watson et al., 1976).

In term of rainfall extrema, 95th daily rainfall has the highest correlation with groundwater recharge (Fig. 2). The 99th daily rainfall also has a positive relationship with groundwater recharge, but with a lower correlation coefficient. It is interesting to note that results for maximum daily rainfall are inconsistent with half of the 310 bores having a positive correlation and another half a negative correlation. This conclusion is consistent with that “a poor correlation between recharge times and maximum intensity of rainfall events” was reported by Masetti et al. (2016).

Both rainfall days (RD) and rainfall intensity (RI, the ratio of annual/seasonal rainfall amount to its corresponding rainfall days) show a positive correlation with groundwater recharge (Fig. 2). However, rainfall days during April-October (RD410) has a slightly better correlation than annual rainfall days (RD) and rainfall days during May-September (RD59). In terms of rainfall intensity, their difference of correlation coefficients with recharge is larger than rainfall days, while April-October rainfall intensity (RI410) has the highest correlation coefficient with recharge.

For total rainfall above a certain threshold, 5mm threshold (R5 and RD5) is the best choice based on correlation coefficients (Fig. 2). The 5mm threshold might be related to interception by vegetation. However, it needs further exploration to make a solid conclusion as interception is affected by many factors and the scope is out of this study. As the threshold increases, the correlation coefficients decrease for both total rainfall and rainfall days. Moreover, a threshold of 40 mm results in a negative correlation between groundwater recharge and total rainfall. This decreasing trend of correlation coefficients with higher thresholds is consistent with the trend of correlation coefficients between groundwater recharge and extreme rainfall varying from 95th, 99th to maximum daily rainfall (35.8mm in this study region).

Groundwater recharge has a positive correlation with wet-spell length and a negative correlation with dry-spell length (Fig. 2). For the wet-spell, mean length has a slightly better correlation with recharge than maximum length, but their difference is minor. In addition, both minimum and maximum correlation coefficients among 310 bores from maximum length of wet-spell are slightly higher than from mean length of wet-spell. Therefore, both of these variables will remain for the further analysis. For dry-spell, mean length has a stronger relation with recharge than maximum length.

Another way to explore the relationship between extreme rainfall and recharge is determine a threshold from all daily rainfall data (e.g., 95th and 99th daily rainfall) and to build a time series of number of days over this threshold (D95 and D99) (Fu et al., 2010). The correlation of this time series with recharge is then assessed. The total annual rainfall (PD95 and PD99) over these days can also be used as an indicator of extreme rainfall. In addition the 95th and 99th threshold can also be defined from wet days only (D95W, D99W, PD95W and PD99W). The results indicate that the number of days over 95th daily rainfall has the highest correlation coefficients (Fig. 2) from this group. With greater extremes, such as 99th, and 95th from wet-day only, the correlation with recharge becomes weaker. This is consistent with previously noted relationship with extreme rainfall.

3.1.2. Temperature and evaporation

The correlations between recharge and temperature/evaporation statistics across 310 bores with a length of 15 years or more (Fig. 3) shows that temperature and evaporation have a relatively weaker relation with recharge than rainfall, but they also could be important factors affecting annual variation of recharge.

For temperature, annual/seasonal means of daily maximum temperature have a negative correlation with groundwater recharge, and annual/seasonal means of daily minimum temperature have a positive correlation with groundwater recharge (Fig. 3). Annual/seasonal means of daily mean temperature have a weaker correlation than both maximum and minimum daily temperature. However, annual/seasonal means of daily temperature range (the difference between daily maximum and minimum temperature) have a stronger correlation with groundwater recharge than both maximum and minimum daily temperature. Moreover, seasonal means over April-October have stronger relationships than annual means.

For evaporation, potential evaporation has a negative relationship with recharge while actual evaporation has a positive relationship (Fig. 3) (Fu et al., 2009). Given similar magnitudes of correlation coefficients from different potential evaporation measures, two popular indicators, pan evaporation and FAO56 potential evapotranspiration, are used for further analysis. With regard to temperature, seasonal means over April-October generally have a higher correlation coefficients than annual means, so potential evaporation over this season are used. It is slightly different for Morton's actual evaporation where annual mean has a higher correlation coefficient than seasonal means.

3.2. Groundwater recharge temporal models

A time series of areal groundwater recharge is obtained by simple averaging all available bores' groundwater recharge for each individual year. This time series is then used to build statistical recharge temporal models with the following steps:

- A statistical recharge model is built with every single variable among all climate variables and three non-climate variables (NDVI, year and groundwater extraction);
- A multiple variable statistical model is built by stepwise regression and best model from all combination; and

- The relative importance technique is used to quantify the contributions of each individual predictor to the multiple regression model.

The time series of corresponding climate variables are obtained in the same way as recharge. For example, for a specific year, if there are only 100 bores having groundwater recharge data, then areal climate variables for that year are achieved only from these 100 bore locations. This provides consistency between averaged recharge and the corresponding variables.

3.2.1. Single variable regression model and its results

Both annual time series of groundwater recharge and its percentage of annual rainfall were used to build the temporal regression models with a single variable. The results (Fig. 4) show that they are similar with overall simple correlation coefficients (Figs 2–3), although it is a single correlation coefficient (Fig. 4) in comparison with 310 at each individual bore (Figs 2–3). In general, recharge percentage of annual rainfall has a lower correlation coefficient with predictors than groundwater recharge itself (Fig. 4), however, there are a few predictors which have higher correlation coefficient with recharge percentage, particularly for negative correlation.

For annual and seasonal total rainfall, rainfall over May-September and April-October still have the highest correlation with groundwater recharge (Fig. 4), but the rainfall during April-October is not the second highest correlation with recharge percentage. JJA seasonal rainfall has almost the same correlation coefficients with recharge and its percentage of annual rainfall, which makes it the second highest correlation with recharge percentage (Fig. 4). DJF rainfall still has a negative correlation with both recharge and its percentage, but its correlation magnitude with recharge percentage (r = -0.26 with p-value = 0.09) are higher than recharge itself (r = -0.14 with p-value = 0.38). In addition, there is a large decrease for annual rainfall from recharge (r = 0.79) to recharge percentage (r = 0.51) (Fig. 4).

For other rainfall statistics and temperature/evaporation, it follows the same patterns as simple correlation at each individual bore site. It seems NDVI does not have statistically significant correlation with either recharge (r = -0.14 with p-value = 0.56) or its percentage of annual rainfall (r = -0.22 with p-value = 0.37) (Fig. 5). This needs further investigation because land use and land cover changes in principal should affect groundwater recharge (Crosbie et al., 2010; Kim and Jackson, 2012; Scanlon et al., 2006). One of possible problems is that the NDVI data we used only has 19 years of data (1992–2012) and misses 3 months (Jan, Feb and Mar) in 1992 and 3 months (Oct, Nov and Dec) in 1994). In addition, NDVI may also be related to irrigation area given this region is dominated by livestock production, dryland and irrigated crop production.

The temporal variable (*year*) has a statistically significant correlation with both groundwater recharge (r = -0.42 with p-value = 0.005) and its percentage of annual rainfall (r = -0.36 with p-value = 0.018) (Fig. 5). This simply implies that both recharge and its percentage have a statistically significant decreasing trend in the last 43 years. Groundwater extraction also has a statistically significant correlation with both recharge (r = -0.43 with p-value = 0.004) and its percentage (r = -0.41 with p-value = 0.007) (Fig. 4). The groundwater extraction in the area of shallow groundwater occurrence may lead to increase in unsaturated zone thickness resulting an increase in recharge. However, its relationship with recharge and its percentage of annual rainfall is weaker than rainfall statistics. This implies that there is an upper limit of recharge determined by rainfall characteristics and thus a sustainable yield exists to maintain sustainable abstraction of groundwater (Sophocleous, 2000) (Doble and Crosbie, 2017).

3.2.2. Step-wise regression results

The results of stepwise regression models are shown in Table 3. Models with 7–9 variables simulated temporal variations of groundwater recharge and its percentage of annual rainfall well with R^2=0.91 (r = 0.95) for groundwater recharge and R^2=0.85 (r = 0.92) for groundwater recharge percentage (Table 3). Groundwater recharge itself was simulated better than recharge percentage of annual rainfall with same or even fewer predictors (Table 3). This is observed for both forward and backward selection methods. Backward selection method of stepwise regression results in two more predictors than forward method for the groundwater recharge model and with a slightly higher R^2 (0.9184 and 0.9077 respectively), but their difference is negligible.

The forward and backward methods result in an eight/nine predictor model for groundwater recharge percentage of annual rainfall, and their coefficients of determination (R^2) are almost the same (0.8476 vs 0.8450). However, two models only have four common predictors. This is evidence of equifinality (Beven, 1993) in that an equally well performing hydrological model can be achieved in many different ways, i.e., different model structure or parameter sets. Here it shows that this also applies to recharge modelling, i.e., different combinations of predictors are equally able to simulate groundwater recharge. It is partly because some candidate variables are highly correlated. The temporal variable (*year*) has only been picked up by the forward method for recharge model, and it was not picked for recharge percentage models from either method.

3.2.3. Best model from all combinations of predictors

The results of best model from all combinations of predictors are shown in Fig 5. For the recharge model, its coefficient of determination improves from 0.80 for single variable to 0.92 for 10 predictors. The seasonal rainfall during April-October (M410) results in the best single variable model and it can explain 80% of variance. However, the best two-variable model come from combinations of M59 (seasonal rainfall during May–September) and SpanM410 (synthetic pan evaporation during April–October). The best four-variable model with variables of M410, M59, MeWS and MxWS can explain 89% of variances, and its 7-variable model is the same stepwise regression with forward method to produce a coefficient of determination of 0.91.

For the recharge percentage model, its coefficient of determination improved from 0.58 for single variable to 0.86 for 10 predictors. The seasonal rainfall during May-September (M59) results in the best single variable model and it can explain 58% of variance. It is interesting to note M410, the best single variable for groundwater recharge amount, is not selected even for a 10-variable model. The best five-variable model with variables of M59, RI410, RD5, MxWS, and SpanM410 can explain 81% of variances (r = 0.90), and these five variables remain in the best model from 6 to 10 variable models. The best 9-variable model is slightly better than stepwise regression results (R^2=0.8513 vs 0.8476 from forward method and 0.8496 from backward method) and has five common predictors with both forward and backward method stepwise regression results.

Given the equifinality issue (Fu et al., 2018), i.e., there are multiple models with different predictor sets that perform equally, it is rational to expand to several best models. Fig. 6 shows the frequencies of each of the variables within the five and ten best models when the number of variables ranges from one to ten. The frequencies are consistent between results of five best models and ten best models. For groundwater recharge model, there are 11 variables having a frequency of 20% or more, and all results of stepwise regression (both forward and backward methods) and best model from all combination with nine-variable or fewer are a sub-set of these 11 variables. The only exception is the 10-variable best model, which has DJF rainfall as a predictor — its contribution is also limited as the coefficient of determination (R^2) only improves from 0.919 to 0.922 when including DJF rainfall (Fig. 6). Based on this frequency, stepwise regression and the best model from all combination, the 7-variable recharge model is our final model with a coefficient of determination R^2=0.908, or correlation coefficient r= 0.953. The temporal variable (*year*) is included in the final recharge model which may imply that some drivers may be missing, but its contribution might be limited, because R^2 of a model without the *year* variable only decreased from 0.908 to 0.902 and its adjusted R^2 changed from 0.889 to 0.886.

For recharge percentage models, the first five variables appear in 56–84% (Fig. 6) of the best models, and all are in the forward stepwise model, four in the backward stepwise model (RI410 is not in the model, but both M410 and RD410 are within the model), and all in the 6-variable best model. Given the first six variables are the same as the best model with 6-variable, and most of them have been selected by stepwise regression model, this is our final recharge percentage model with a coefficient of determination R^2=0.833, or correlation coefficient r=0.913.

Surprisingly, the diurnal temperature range (Tdiff) was the most important single non-rainfall climate variable for groundwater recharge (Fig. 3−4), but it was not selected by the stepwise regression, or in the best model from all combinations of predictors. It could be because it has a higher correlation with rainfall statistics.

3.2.4. Relative importance of groundwater recharge models

The relative importance results (Fig. 7) indicates that each of M59 and M410 contribute about one-third to the coefficient of determination for the recharge model. It is not surprising because each of them alone can explain about 80% of variance with a single parameter recharge regression model (Fig. 4). The length of wet spell, both mean and maximum lengths, contribute about one-quarter of coefficient of determination. These are the four most important predictors — if we build a recharge regression model with these four parameter only, it can explain 88.6% of variance with an adjusted R^2 value of 0.874. It is very close to the full model with a R^2 of 0.908 and an adjust R^2 of 0.889. The other three variables, i.e., Morton's actual evaporation, groundwater extraction and *year*, contribute between 3.6–4.6% each. But it can be as high as 10% or as low as 0.6% among 1000 boot strapped resample simulations.

For recharge percentage models, M59 is still the most important variable. But the contribution decreases from 32% (groundwater recharge amount model) to 27% (groundwater recharge percentage model). The maximum length of wet-spell and mean rainfall intensity during April-October each contributes about 20%. The other three variables (R5, FAO56 potential evapotranspiration and synthetic pan evaporation) contribute between 10–13% each to the groundwater recharge percentage model.

3.3.Groundwater recharge spatial models

3.3.1. Climate and non-climate numeric variables

Fig. 8 shows the groundwater recharge spatial model with 38 rainfall statistics. The correlation coefficients are much lower than those for the groundwater recharge temporal model (Fig. 5a). Part of the reason results from the sample size being only 43 (1970–2012 years) for a temporal model but 426 for a spatial model. There are still a number of rainfall statistics that result in a statistically significant models for both groundwater recharge and its percentage of annual rainfall. The most significant rainfall statistic is maximum length of wet-spell with r=0.170 and *p-value* = 0.001. Most rainfall statistics, except DJF rainfall and both mean and maximum lengths of dry-spell, have a positive correlation with recharge spatially. However, all rainfall statistics, except mean length of dry-spell, have a negative relation with recharge percentage of annual rainfall. It is quite different to recharge temporal models (Fig. 4a), which show a majority of rainfall statistics have the same correlation direction with both recharge and its percentage.

Fig. 9 shows the recharge spatial model with temperature and evaporation. The correlation coefficients are also lower than those of the recharge temporal model (Fig. 4b) and suffer the same sample size differences as before, i.e., 43 (1970–2012 years) for a temporal model and 426 for a spatial model. However, their differences are relatively smaller than those of rainfall statistics. The most significant temperature/evaporation variables are the seasonal (May-Sep) means of daily pan evaporation with r = -0.233 and *p-value* = 0.000 for recharge models, and annual/seasonal (May-Sep) means of diurnal temperature range with a r = 0.334 and *p-value* = 0.000 recharge percentage models (Fig. 9). Notably, annual/seasonal means of daily minimum temperature and diurnal temperature range are overall two most important variables and both of them have the same correlation direction with both recharge and its percentage for all three time periods (annual, May-September and April-October). For other variables, they have a negative relation with groundwater recharge spatially, and a positive relation with recharge percentage of annual rainfall (Fig. 9).

All temperature and evaporation variables, except annual/seasonal means of diurnal temperature range, have a negative relation with recharge. This is quite different to recharge temporal models (Fig. 4b), where annual/seasonal means of daily maximum temperature have an opposite sign with those of daily minimum temperature, and potential evaporation has an opposite sign with actual evaporation (Fig 4b).

Fig. 10 shows the recharge spatial model with a few non-climate numeric variables, including longitude, latitude, NDVI, mean ground water level, mean ground water depth, and groundwater extractions. It is interesting to note that mean groundwater depth has the highest correlation with recharge in space, which is higher than any other climate variables (rainfall, temperature and evaporation). It also has the second highest correlation coefficient for the recharge percentage spatial models -- only behind annual/seasonal means of diurnal temperature range and same magnitude as the annual/seasonal means of daily minimum temperature. It might imply the caveats of current studies in the literature about the climate change impacts of groundwater recharge. If the climate change results in a decline in regional rainfall, especially rainfall statistics having a high correlation with groundwater recharge, then it will result in a decrease of groundwater recharge and a decline of groundwater level (or increase of groundwater depth) in the future. This will then magnify the impacts from the deeper water table, and accordingly produces a positive feedback.

Further investigation indicates that the relationship between recharge and the mean water table depth (Fig. 11) is non-linear: when the water table is shallow (e.g., less than 2 meters), the recharge and its percentage will increase with groundwater depth (Fig. 11). This is because a near-surface water-table leaves little space for recharge and most rainfall will convert into surface runoff and evaporation, while a relatively deeper groundwater depth will allow more capacity for recharge. However, when the water table is deep (e.g., deeper than 2 meters), the recharge and its percentage will decrease with groundwater depth (Fig. 11). The available space is no longer a limitation in this case, and a deeper groundwater level will result in less rainfall reaching the water table, and accordingly smaller recharge and rainfall percentage. This conclusion is consistent with a recent result of Doble and Crosbie (2017), which reviewed the current and emerging methods for catchment-scale modelling of recharge and evapotranspiration from shallow groundwater.

3.3.2. Soil and land attributes

The correlation coefficients between long-term means of annual recharge and soil/land attributes among 426 groundwater bores (Table 4) shows that nine out of ten soil/land attributes have a statistically significant correlation with groundwater recharge at α=0.05 level. The remaining one has a *p*-value of 0.056, which means that it is statistically significant at α=0.06 level. The magnitude of correlation coefficient are much higher than those between recharge and climate and non-climate numeric variables (Figs 7–9). It indicates that dominant factors for recharge spatial models are soil and land attributes (Crosbie et al., 2010; Kim and Jackson, 2012; Scanlon et al., 2006), which is different to recharge temporal models. It is straightforward to understand, because for a recharge temporal model in 50 year period, its soil and land attributes are relatively stable and accordingly its variation mainly comes from climate variables (Figs 2-4).

It is also interesting to note that the more detailed the categories of a soil/land attribute are, the higher correlation coefficients are between them and recharge. Land System, which is based upon groupings of Soil Landscape Map Units, has the highest correlation with recharge. It is because it is broad and readily recognisable landscape features defined by particular and distinctive patterns of land use, geology, topography, soils and vegetation within a limited climatic range (https://data.sa.gov.au/data/dataset/land-systems). There are 864 land systems have been described within southern South Australia within the hierarchical mapping framework and 70 of them are found in our research area.

The "Depth to Water Table" category attributes shows similar results with numeric groundwater depth reported in the previous section (Fig 11). However, this category information is derived from soil landscape mapping and not a specific watertable survey. Therefore, it could have a significant amount of estimation based on the local knowledge of land resources specialists (https://data.sa.gov.au/data/dataset/watertable). In addition, all area with a water-table deeper than 2m is classified as the same category.

The correlation coefficients between long-term means of recharge percentage and soil/land attributes among 426 groundwater bores (Table 4) shows that all ten soil/land attributes have a statistically significant correlation with recharge at α=0.05 level. Moreover, all p-values are < 0.001, which mean they are statistically significant even at α=0.001 level. The correlation coefficients with recharge percentage are generally larger than those with groundwater recharge itself.

3.4.Groundwater recharge trend and its attributions

Overall, the recharge and its percentage of annual rainfall shows a decreasing trend over the last 43 years (Fig. 12). All rainfall statistics which have a positive relationship with recharge have been decreasing during the study period, and all rainfall statistics which have a negative relationship with recharge have been increasing. Given that rainfall is the primary driver for recharge, these changes results in a decline of recharge. Moreover, three (M410, MeWS and MxWS) of the four most significant combined variables identified in this study, which can explain 88.6% of variance (or r=0.94) of recharge, have shown a statistically significant decreasing trend.

3.5.Uncertainties

3.5.1 Groundwater recharge estimation

The groundwater recharge dataset used in this study is estimated with the water-table fluctuation (WTF) method, and accordingly it has the inherent assumptions and limitations of the WTF method (Healy and Cook, 2002): 1) the observed hydrograph of bores represents only natural water-table fluctuations caused by groundwater recharge and discharge; 2) the specific yield is known and constant over the calculated time period; 3) the pre-recharge water-level recession can be extrapolated to determine the change in height of the water table.

To ensure that the water table rises used in the WTF estimates of recharge are only caused by natural recharge, any bores that were in irrigation areas or subject to pumping have been excluded from analysis.

The greatest source of uncertainty in the WTF estimates of recharge used here is the assumption that the specific yield is 0.1 for the entire region. From equation (1) it can be seen that any error in the specific yield translates linearly to an error in the recharge estimates. Although this is neglecting any heterogeneity throughout the region, it is the best information currently available (Brown et al., 2006; Crosbie and Davies, 2013). As the temporal pattern of recharge is determined by the change in groundwater levels and is not dependent on the specific yield, the uncertainty in the recharge estimates due to the specific yield do not affect the conclusions of this paper that rely on the temporal trend in the recharge data.

3.5.2 Climate and non-climate Data

The climate dataset used in this study was interpolated from approximately 4600 locations across Australia, which is provided by the Bureau of Meteorology (BoM). There are two sources of potential uncertainties: observation errors, such as untagged weekend accumulations identified by Viney and Bates (2004), and interpolation errors.

Clearly groundwater extraction is one of major drivers resulting in groundwater head variation, and accordingly groundwater recharge accuracy. Unfortunately, detailed information of groundwater extraction is not available. The only available groundwater extraction dataset, developed by Harrington and Li (2015), was estimated on the assumption that the average annual groundwater extraction rate for an individual bore to be constant over time. Therefore, it cannot be used for groundwater recharge temporal modelling at each individual site. It clearly introduces uncertainties in the presented results.

Impacts of land-use and land cover changes on groundwater recharge have been widely demonstrated in the literature across diverse environmental settings, including agriculture activities and forest plantation and clearance (Adane and Gates, 2015; Dean et al., 2015). The NDVI was used in this study, but the results showed that its relationship with recharge was lower than most climate and non-climate variables (Figs 4 and 9). A further investigation is needed to explore the detailed dynamics of land use and land cover change, especially forest plantation and clearance, as well as its relationship with recharge to reduce the uncertainties.

3.6.Implications for future climate change impact on groundwater recharge

This method demonstrated here can be easily used for a different study region and the results of this study could serve as a reference for climate change and variability impacts on groundwater studies, particularly for regional groundwater management and planning under future climate changes in the study region. For example, future climate projections for the study region have a high confidence for less Apr–Oct rainfall under both RCP4.5 and RCP8.5 emission, as well as a very high confidence for increased temperatures and consequently potential evaporation. This, based on the controlling factors identified in this study for recharge, would suggest that recharge will continue to decline into the future. This is also consistent with previous modelling of future recharge based on future climate projections from CMIP3 (Crosbie et al., 2013). The relationship between recharge and groundwater depth could potentially leads to a further reduction in recharge due to its positive feedback loop of declining recharge. However, it is clearly not a monotonic linear trend due to its complicated non-linear relationship and the teleconnection between recharge and large-scale circulation patterns. Future works will explore some complicated models, such as the Bayesian spatial model combining time-dependent approach (Stevenazzi et al., 2017).

4. Conclusion

- Rainfall is clearly the most important factor for recharge, but this study show that some rainfall statistics are more critical for recharge than annual rainfall. For example, seasonal rainfalls from May to September (M59) and April to October (M410) are more highly correlated with recharge than annual rainfall.
- In contrast, DJF seasonal rainfall has a negative correlation with recharge. This suggests that a seasonal shift in rainfall towards summer could result in a decrease of recharge even if the annual rainfall keep unchanged.
- Wet spell lengths, both mean (MeWS) and maximum (MxWS), are also critical for recharge. These four parameters explained 88.6% of recharge temporal variance, almost equivalent to the optimum model of seven metrics that reproduced 91% of the variance.
- The mean groundwater depth has a statistically significant correlation with recharge spatially, stronger than climate variables/statistics. This relationship implies a positive

feedback between declining rainfall, reduced recharge and reduced groundwater levels that magnifies the impact of climate change, suggesting literature using historical relationships between rainfall and recharge may underestimate the impact of climate change.

- Nine out of ten soil/land attributes have a statistically significant correlation with recharge at α=0.05 level, and all of them have a statistically significant correlation with recharge percentage at α=0.001 level. Their magnitudes of correlation coefficient are much higher than those between recharge and climate and non-climate numeric variables.
- Overall, the recharge and its percentage showed a statistically significant decreasing trend over the last 43 years, which can be explained by the factors identified in this study.
- The methods here could be easily applied in a different regions to investigate the relationship between groundwater recharge and its controlling factors, and the findings of this study could also have implications on projecting the impacts of climate changes and variability on groundwater resources by selecting suitable GCMs from important rainfall statistics.

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List of Figure Captions

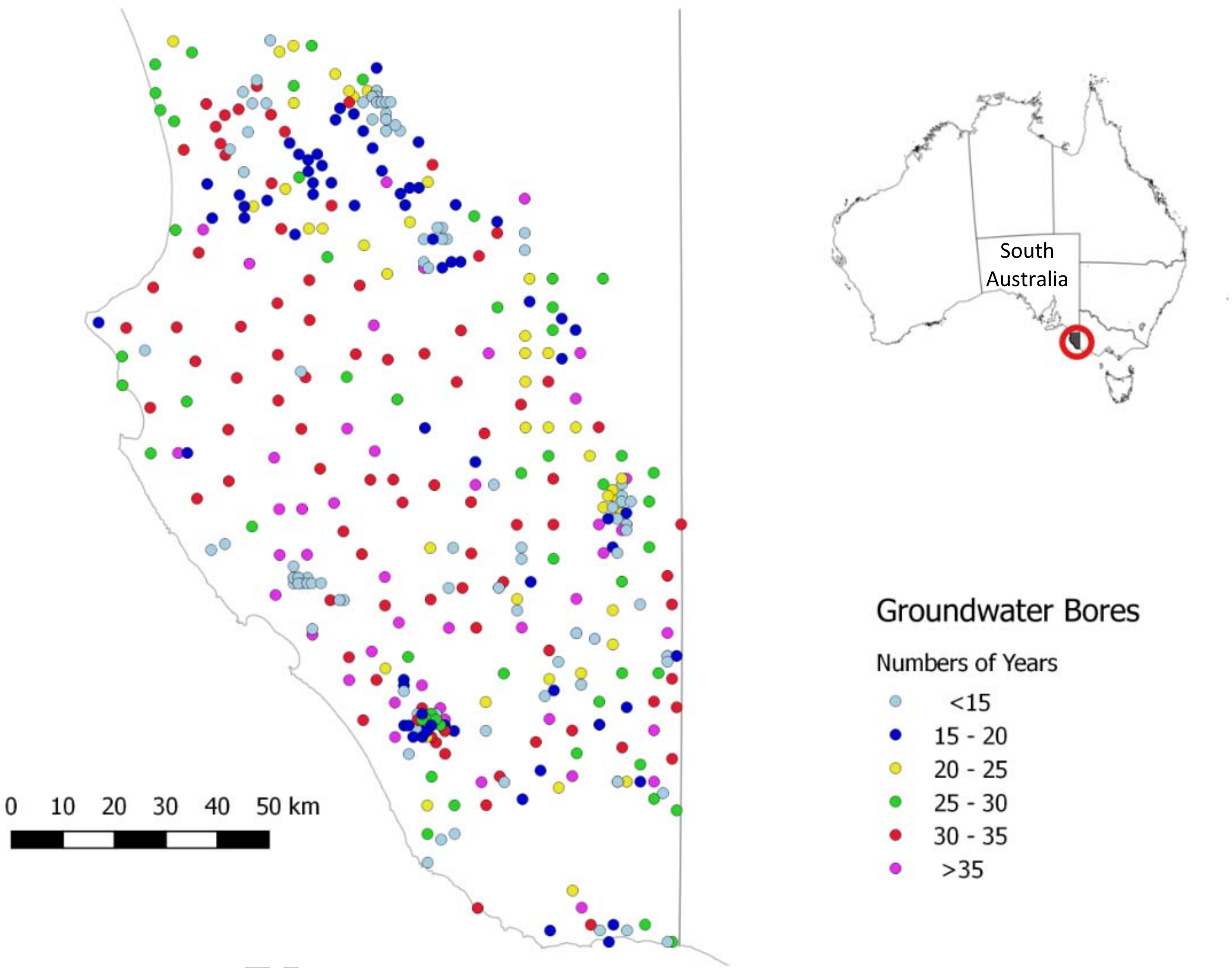


Fig 1 Location of study region and 426 groundwater bores

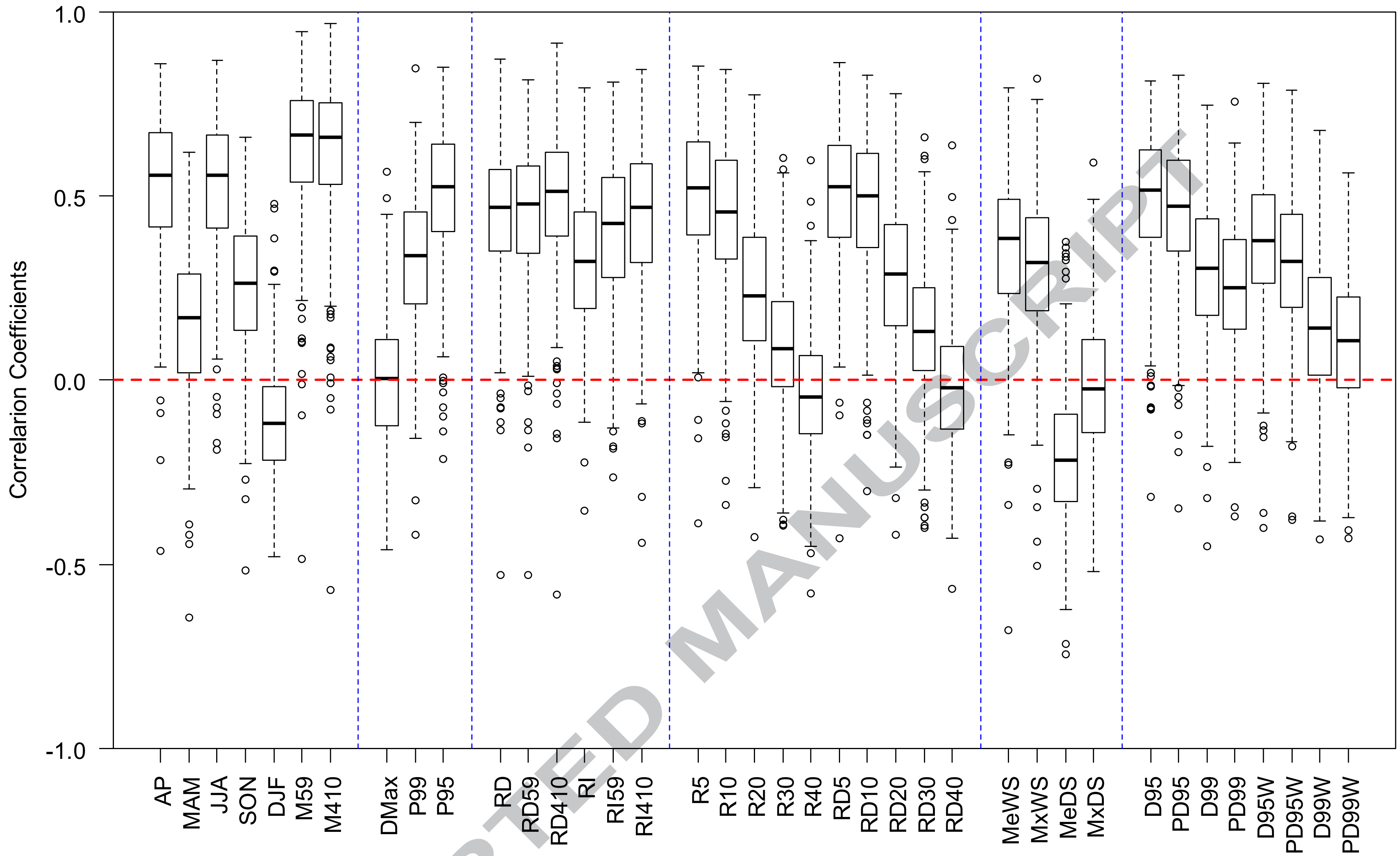


Fig 2 Correlation coefficients between groundwater recharge and 38 rainfall statistics across 310 bores

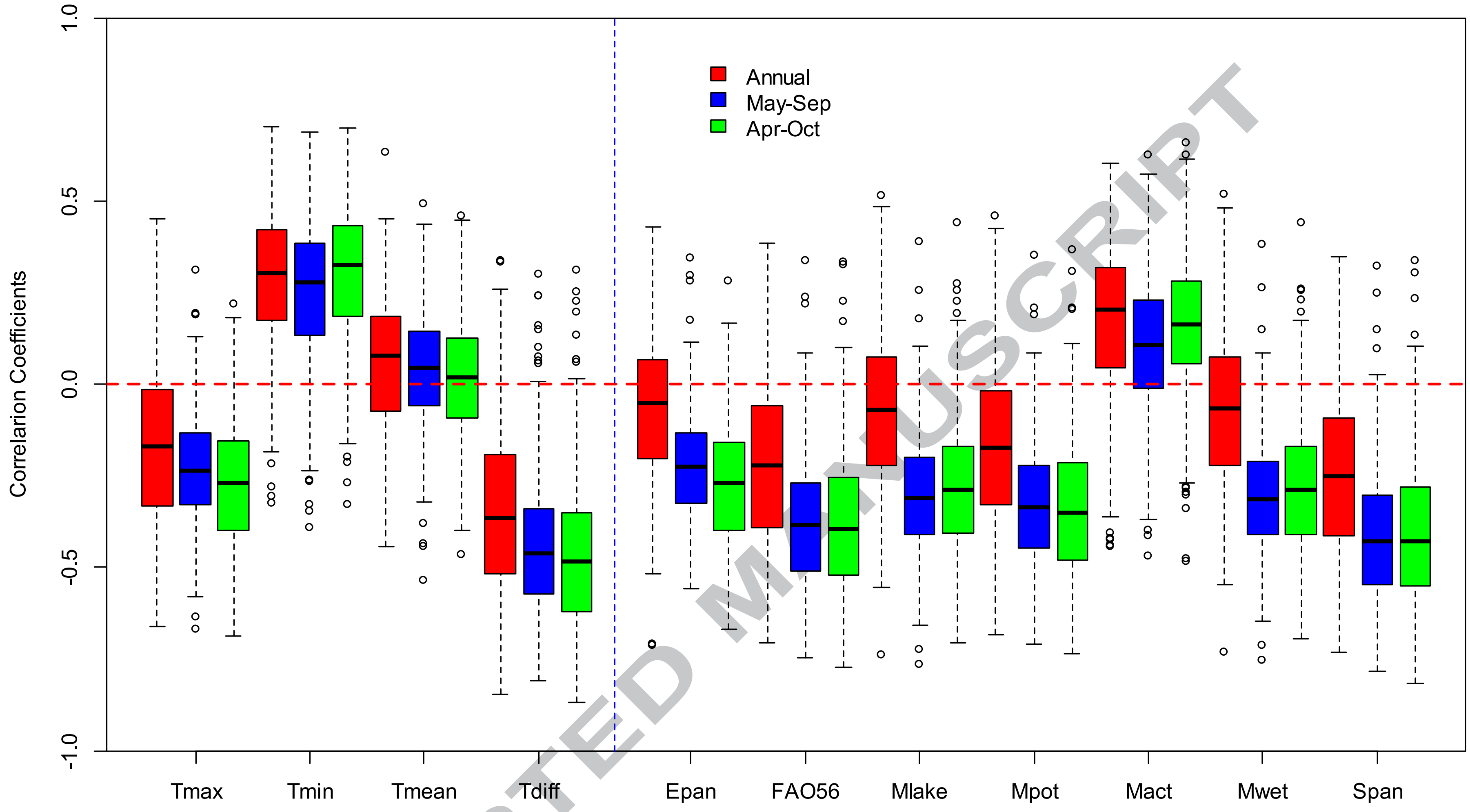
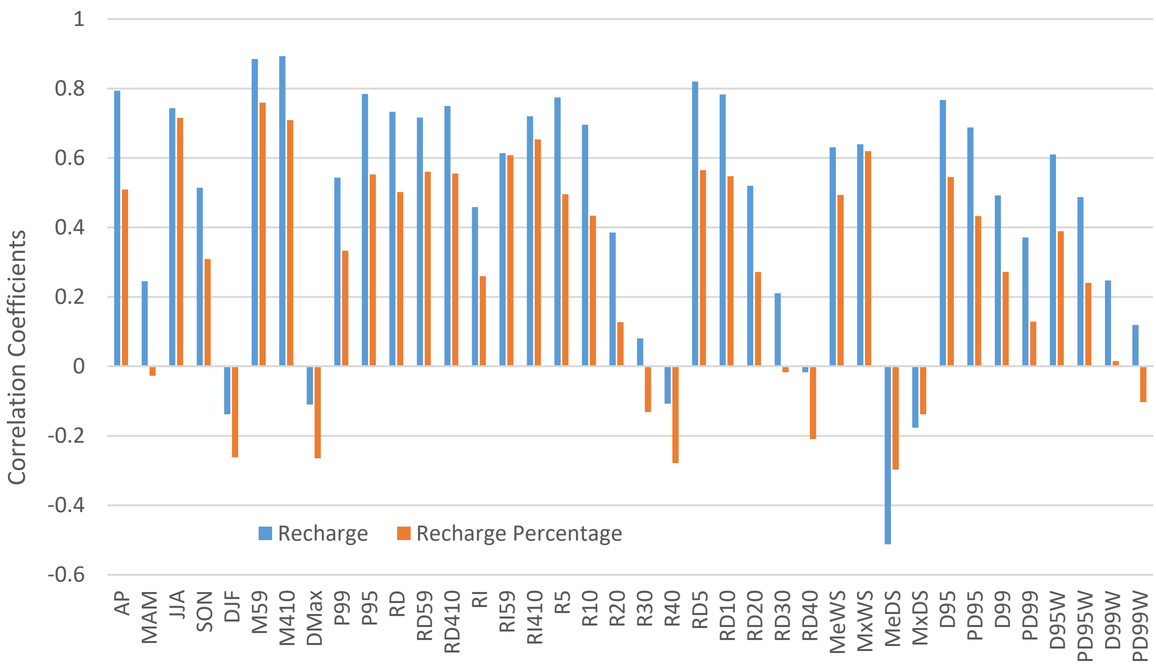


Fig 3 Correlation coefficients between groundwater recharge and temperature/evaporation across 310 bores



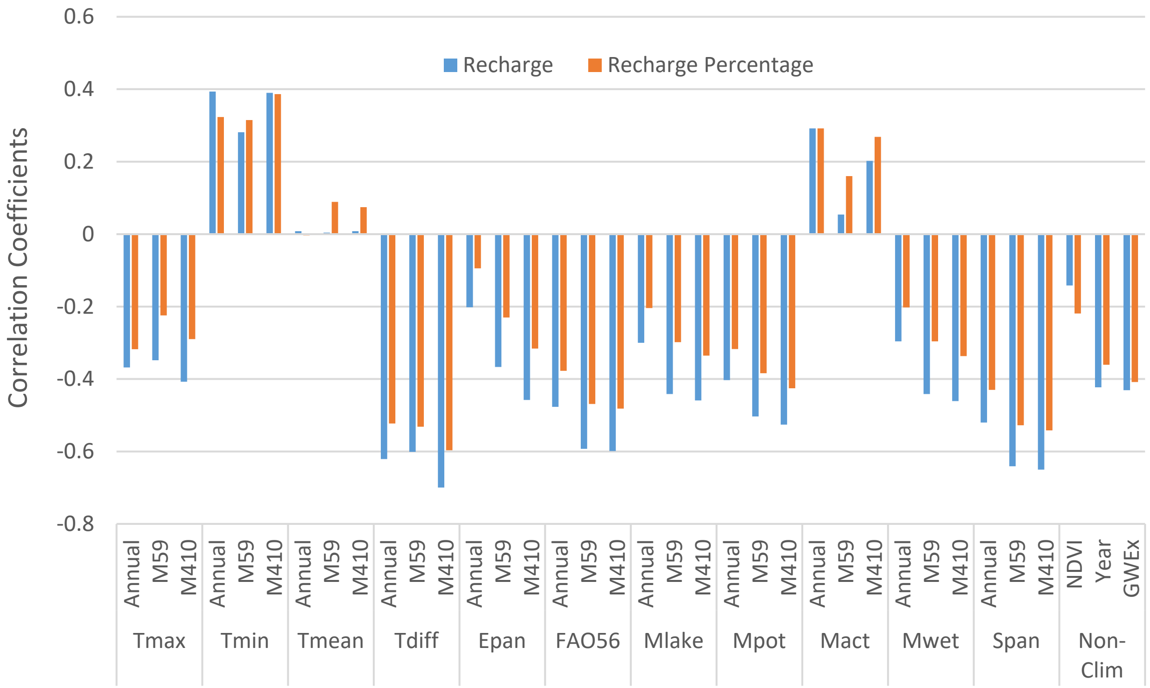


Fig 4 Correlation coefficients between areal groundwater recharge and climate and non-climate variables

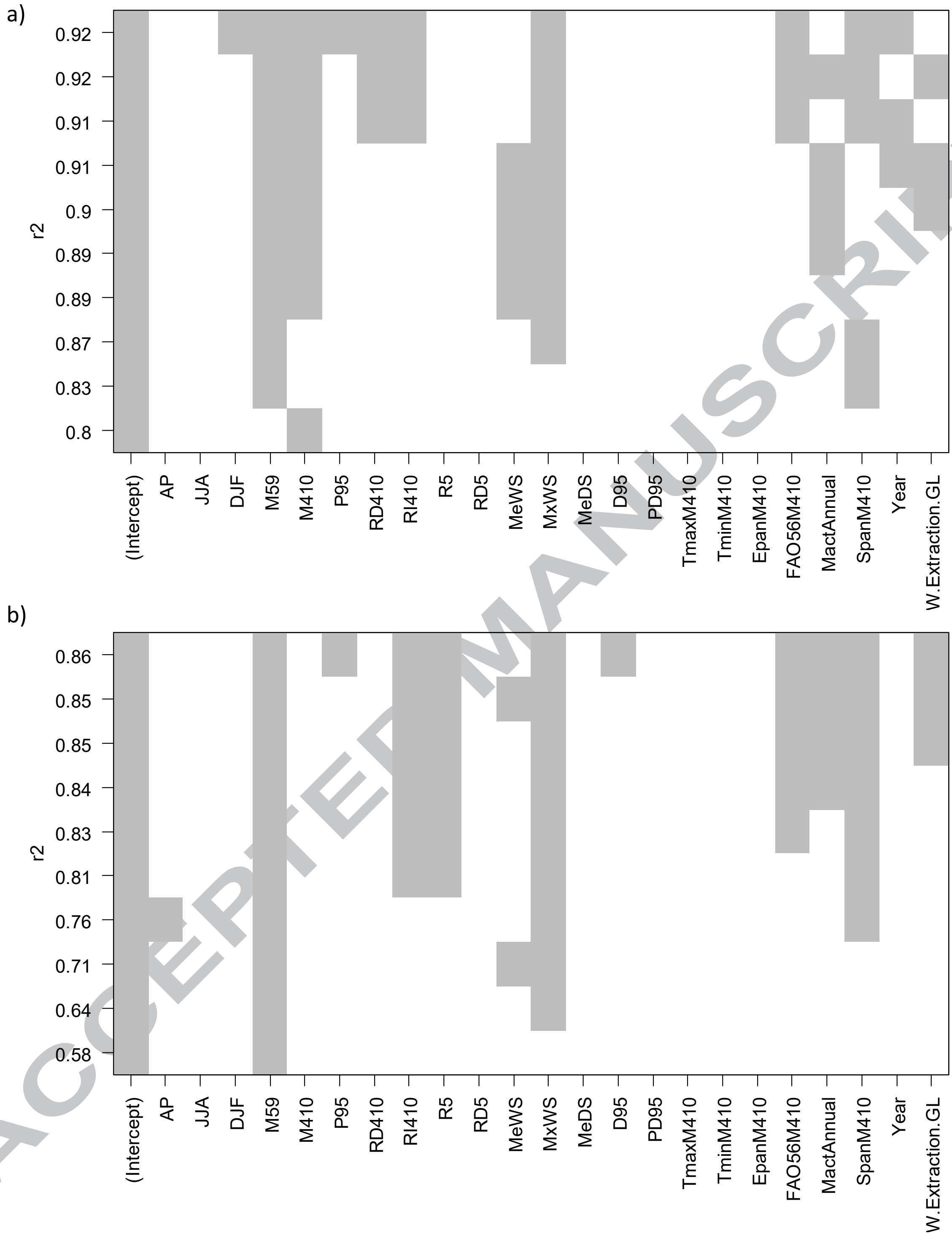


Fig 5 Best model from all combination of potential predictors for a) groundwater recharge and b) recharge percentage of annual rainfall

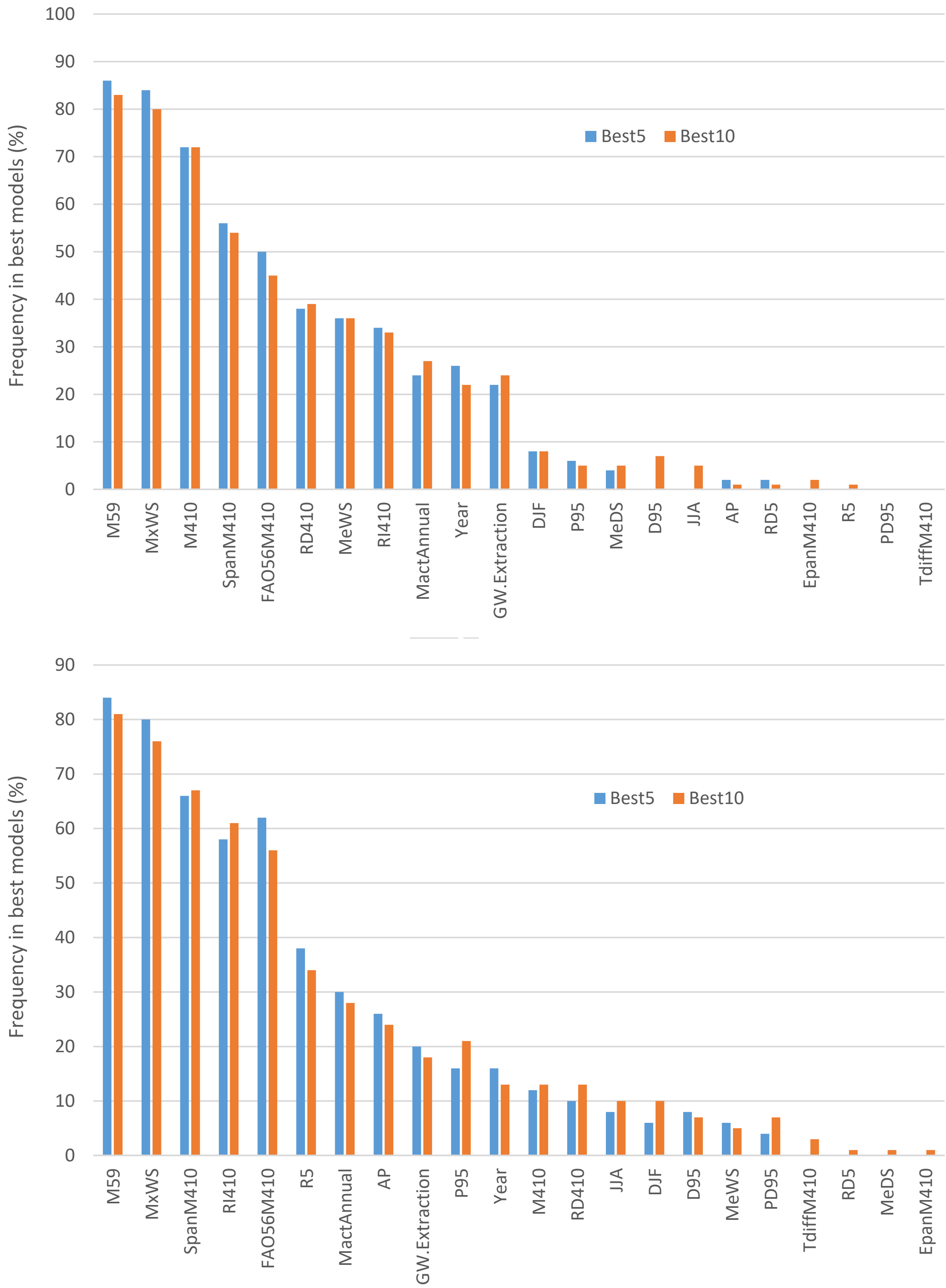


Fig 6 Frequency of main variables in best models (%) for a) groundwater recharge model and b) recharge percentage model

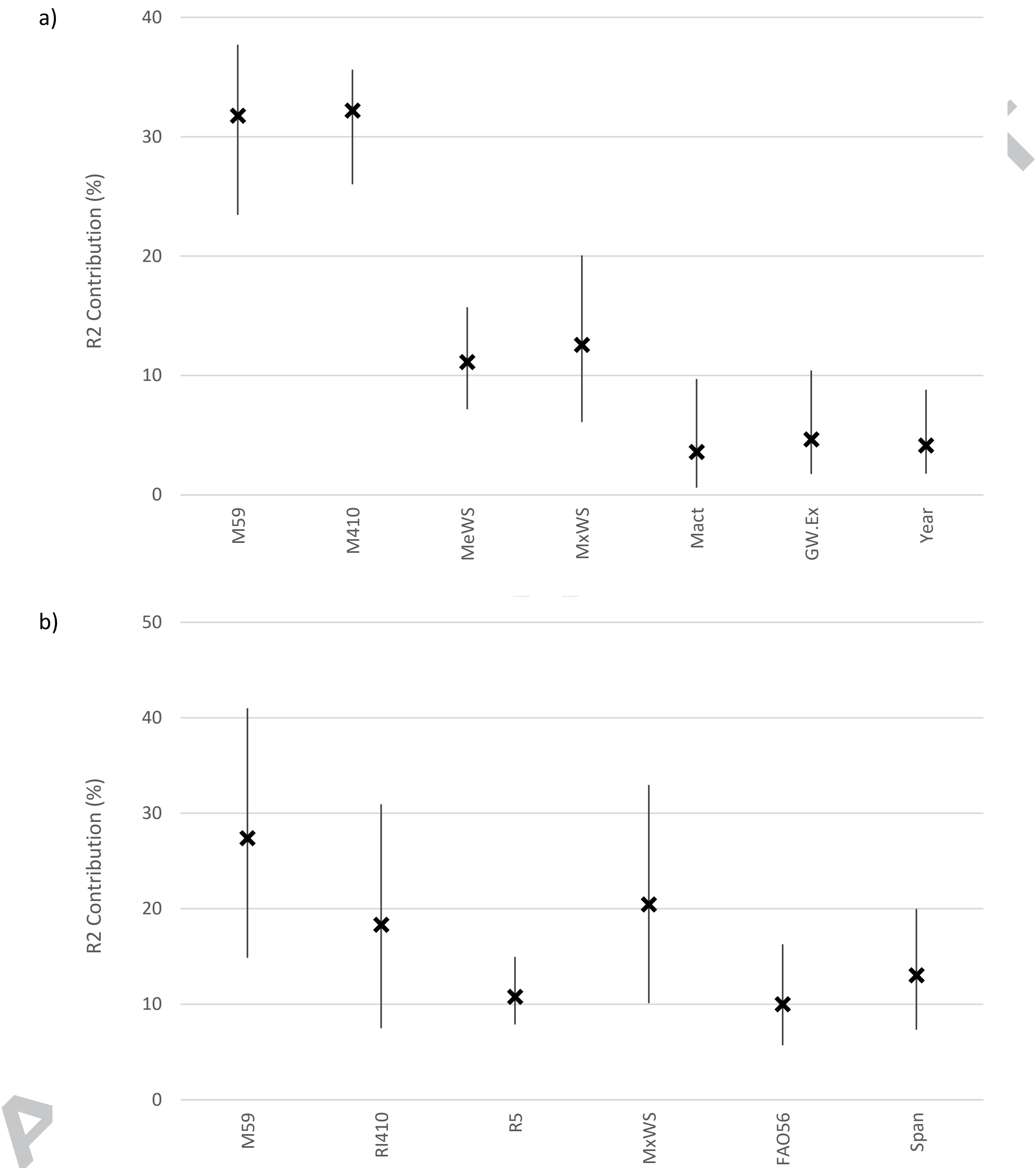


Fig 7 Relative contribution to R^2 from each of predictors in the a) groundwater recharge model and b) recharge percentage model

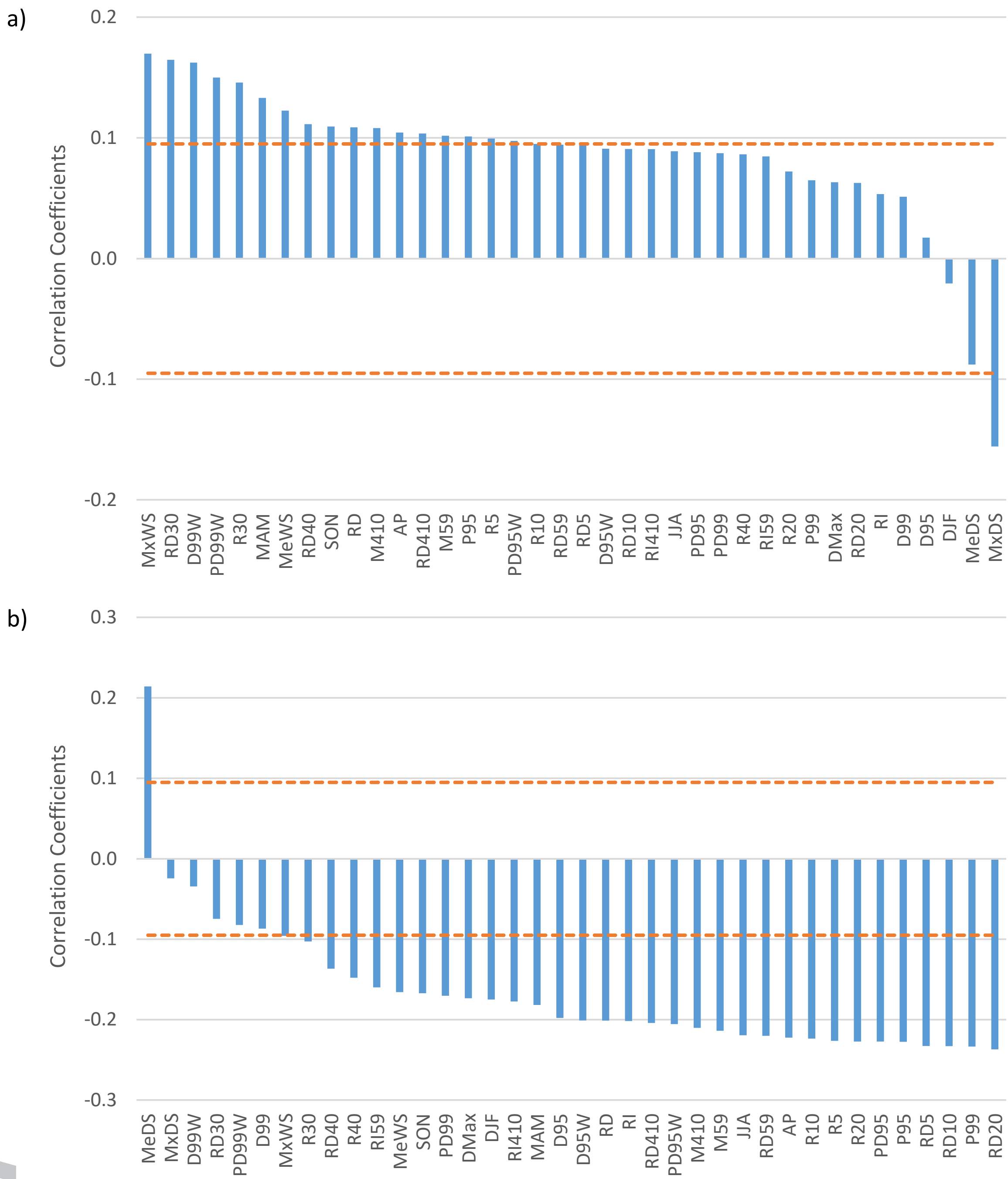


Fig 8 Correlation coefficients between: a) groundwater recharge and b) groundwater recharge percentage and rainfall statistics among 426 groundwater bores. The dash lines indicate the statistical significance at α=0.05

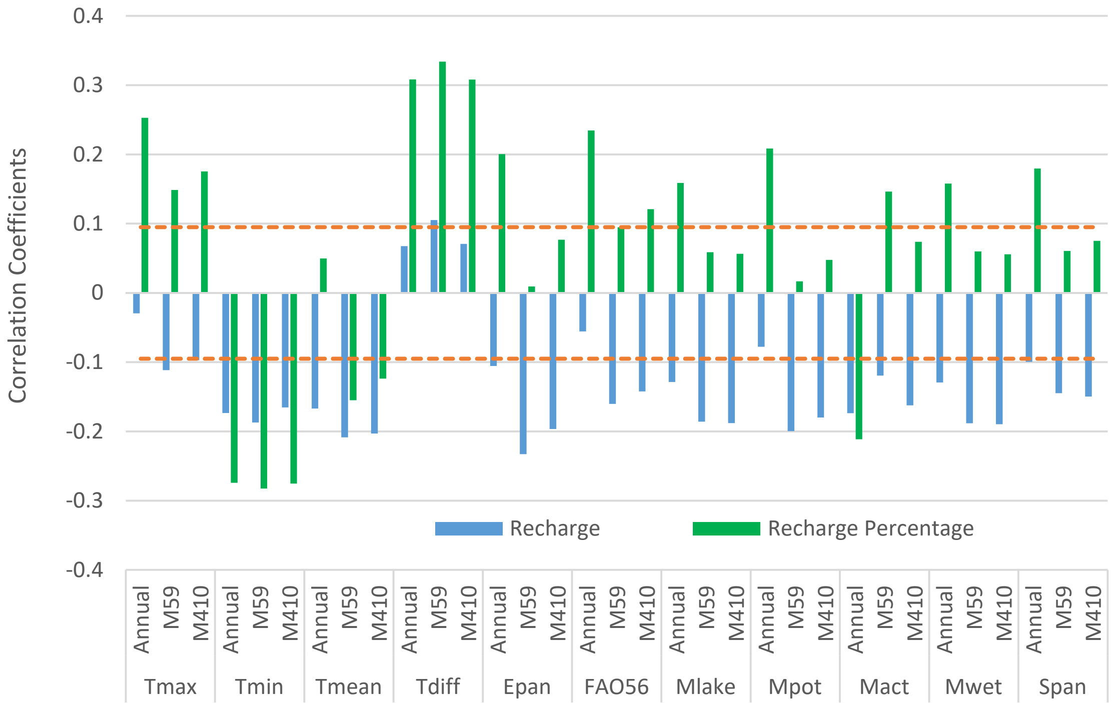


Fig 9 Correlation coefficients between groundwater recharge/groundwater recharge percentage and temperature/evaporation among 426 groundwater bores. The dash lines indicate the statistical significance at α=0.05

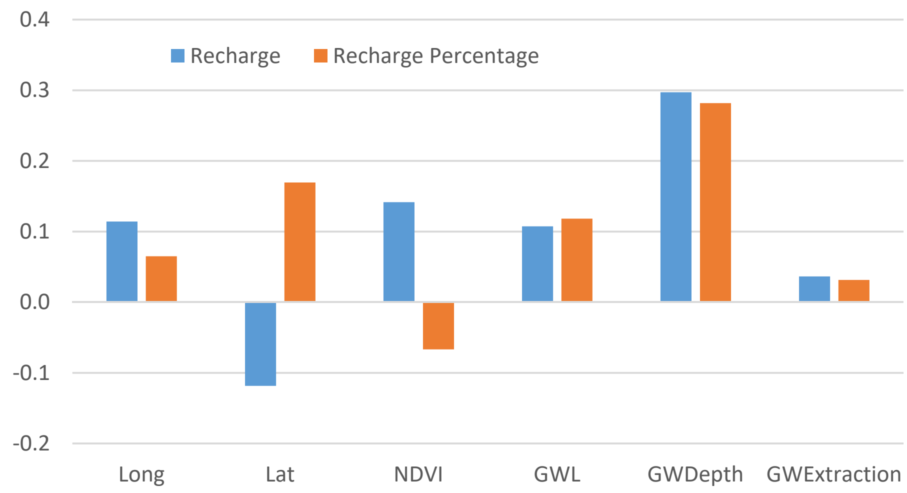


Fig 10 Correlation coefficients between groundwater recharge/groundwater recharge percentage and non-climate numeric variables among 426 groundwater bores.

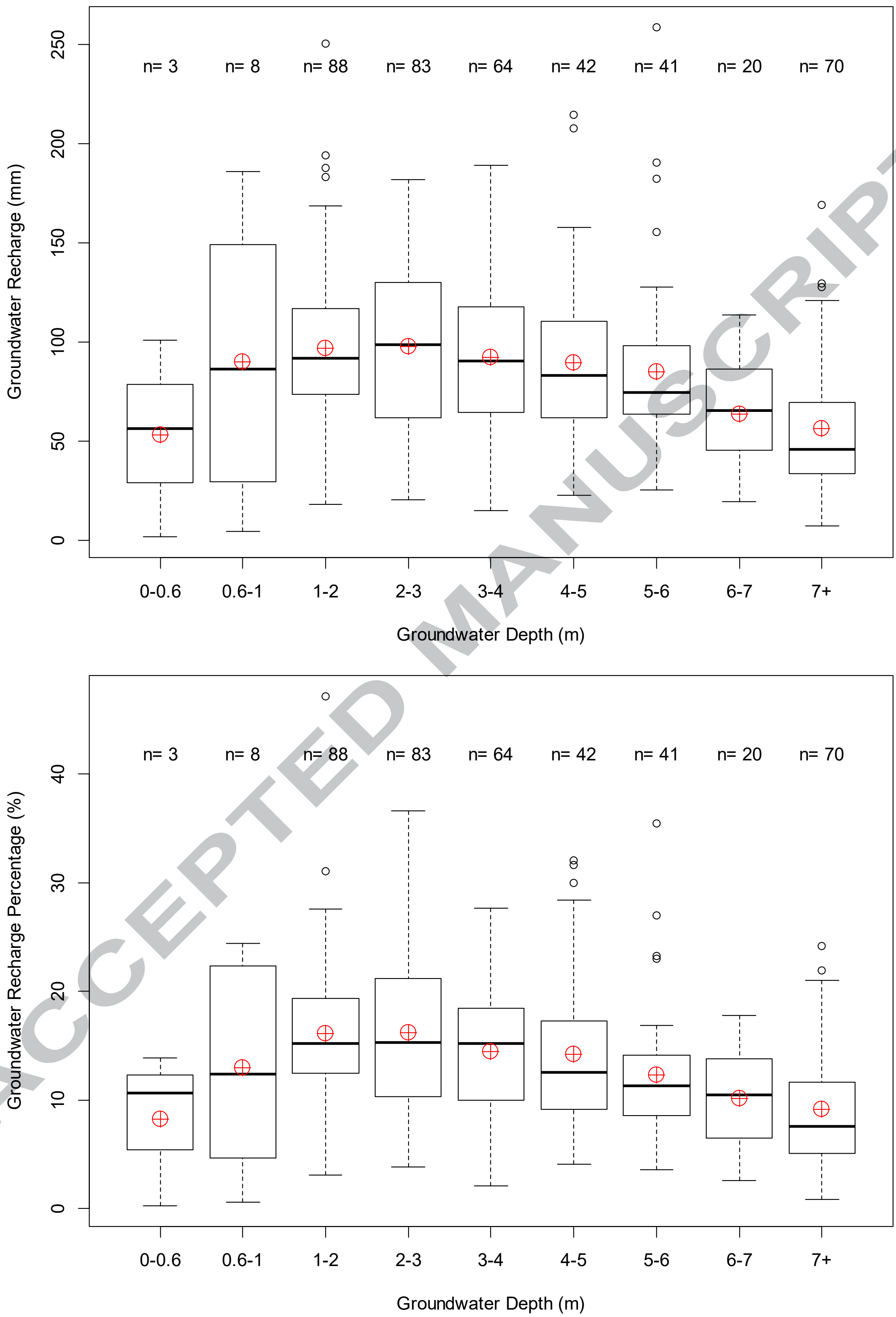


Fig. 11 Correlation coefficients between groundwater recharge/groundwater recharge percentage and groundwater depth among 426 groundwater bores.

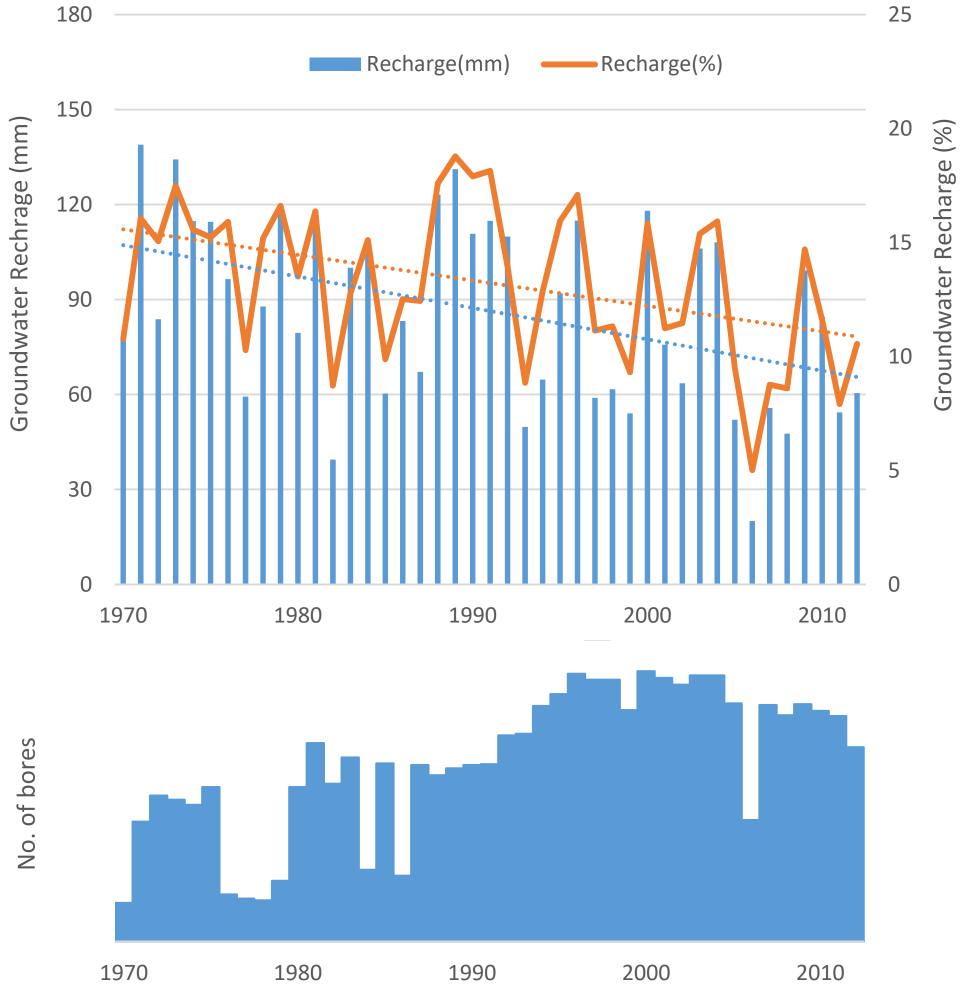


Fig. 12 Times series of groundwater recharge and its percentage of annual rainfall and numbers of groundwater bores in each year from 1970 to 2012

Table 1 Summary of relevant literature on climate change impacts on groundwater resources

Study	Approach/Model	Location	Key results
1. Taylor et al. (2013)	• Comprehensive review	Worldwide	• Review of recent researches on the impacts of climate on groundwater; • Examination of the opportunities and challenges of groundwater resources under climate adaptation strategies; • Limitations of understanding of the dynamic relationship between groundwater and climate.
2. Smerdon (2017)	• Review		• Six review articles on groundwater and climate change are briefly summarized.
3 Green et al. (2011)	• Comprehensive review		• The challenge of understanding and predicting a number of interrelated variables in space and time are described; • Many observational techniques spanning isotopic, geochemical, geophysical and remote sensing methods that could be useful in observing large-scale changes in groundwater are documented; • Several of the first studies that attempted to quantitatively link climate (or weather) models with hydrologic models are reviewed.
4. Meixner et al. (2016)	• Review	8 aquifer systems, Western USA	• Recharge components are compared across the selected aquifers; • Climate-change is analyzed to determine impact on total recharge and mechanism; • Geographical patterns in total recharge and mechanism changes are described; • Knowledge gaps that limit predictions of future changes in recharge are identified.
5. Klove et al. (2014)	• Review		• Review on climate change effects on groundwater and dependent ecosystems.
6. Chen et al. (2002)	• An empirical model that links annual precipitation and temperature to groundwater level; • Historical data.	Southern Manitoba, Canada	• Annual average water level is positively correlated to annual precipitation with a certain time delay in most observation wells; • The water level variation displays a correlation with the annual average air temperature for most of the monitoring wells, but weaker correlation than precipitation
7. Gong et al. (2012)	• A simple soil-water balance method; • Historical data.	Yanqing Basin, Beijing, China	• The variation of groundwater recharge follows precipitation changes; • Land use plays a more influential role in groundwater recharge than soil texture; • The water table quickly rises in response to recharge in the shallow parts of the aquifer.
8. Zhang et al. (2016)	• Soil Water Balance Model • Historical Data	Northern High Plains Aquifer, central United States	• Extreme precipitation plays a significant role in determining groundwater recharge; • Recharge was more sensitive to extreme precipitation than total rainfall.
9. Nasta et al. (2016)	• PCR-GLOBWB model • Historical Data	Africa	• The different effects of climate-change controls on potential groundwater recharge were detected as a function of latitude; • The increase in temperature is significantly correlated to the decline of potential groundwater recharge, especially in the Northern Equatorial Africa; • The climate indicators considered were unable to explain the alarming negative trend of potential groundwater recharge observed in the Sahelian region;

			• A strong seasonality effect is observed, i.e., potential groundwater recharge is in-phase with rainfall patterns in the summer (Northern Hemisphere) and winter (Southern Hemisphere) and out-of-phase during the fall season.
10. Thomas et al. (2016)	• Data analysis from historical precipitation, groundwater table and streamflow	Southwestern United States	• Significant changes in the recharge/precipitation ratio is concurrent with decreases in precipitation intensity.
11. Barron et al. (2012)	• Recharge model: Slightly modified WAVES • Statistical analysis on the effects of climate characteristics on modelled recharge	A range of Köppen-Geiger climate types in Australia	• The correlation between the modelled recharge and total annual rainfall is weaker than that between recharge and rainfall intensity; • Annual recharge is greater in winter-rainfall regions than summer-rainfall regions if the soil and annual rainfall are the same; • The climate parameters (such as solar radiation and vapour pressure deficit) rather than rainfall have the highest recharge impacts in the tropical climate type.
12. Scibek and Allen (2006)	• Recharge model: HELP • Groundwater flow model: MODFLOW • Future climate: 1 GCM + Downscaling	South central British Columbia, Canada	• Future climate changes will result in more recharge to the unconfined aquifer from spring to the summer season; • The overall effects of recharge on the water balance is small because of dominant river-aquifer interactions and river water recharge.
13. Jyrkama and Sykes (2007)	• Recharge model: HELP3 • Future climate: Scenarios of precipitation, temperature and solar radiation changes	Grand River,Ontario, Canada	• The overall rate of groundwater recharge is predicted to increase as a result of climate change; • The impacts have high spatial variability.
14. Goderniaux et al. (2009)	• Surface-subsurface flow model: HydroGeoSphere • Future climate: 6 RCM	Geer basin, Belgium	• Significant decreases are expected in the groundwater levels (up to 8 m) and in the surface water flow rates (between 9% and 33%) by 2080.
15. Crosbie et al. (2011)	• Four hydrological models: WAVES-G, WAVES-C, HELP, and SIMHYD • Future climate: 5 GCMs + 3 downscaling methods	Southern Australia	• The choice of GCM is the largest source of uncertainty; • The downscaling method is the next largest source of uncertainty; • The choice of hydrological model is the source of the least uncertainty.
16. Liu (2011)	• Ecohydrology-based approach • Future climate: 3 scenarios of changes of rainfall intensity, frequency, and depth	*Yucca Mountain*, Nevada, USA	• Both groundwater recharge and deep-rooted vegetation coverage increase with decreasing rainfall frequency (for a given amount of annual rainfall), with increasing average rainfall depth per rainfall event (for a fixed frequency) and with increasing frequency (for a fixed rainfall depth per rainfall event).
17. Ali et al. (2012)	• Recharge model (VFM) linked with three groundwater models: PRAMS, SWAMS (MODFLOW), PHRAMS. • Future climate: 15 GCM + daily scaling method	South-western Australia	• The reduction in groundwater recharge is expected to impact all other components of the water balance; • The groundwater discharge to the ocean and natural drainages is expected to reduce substantially under the dry future climate; • Storage changes are most sensitive to climate change while net leakage to confined systems is least sensitive.
18. Crosbie et al. (2013)	• Recharge model: 1D WAVES • Future climate: 16 GCMs with 3 emission scenarios = 48 variants	Australian continent at a 0.05° grid resolution	• The median results project a reduction in recharge across the west, centre and south of Australia and an increase in recharge across the north and a small area in the east of the continent; • The range of results is quite large and for large parts of the continent encompasses both increases and decreases in recharge.

19. Kurylyk and MacQuarrie (2013)	• Recharge model: HELP3 • Future climate: GCM + downscaling	Otter Brook, central New Brunswick, Canada	• Future projections for groundwater recharge are highly uncertain; • This uncertainty stems primarily from the variability in climate projections; • The recharge was most sensitive to the choice of the post-processing method; • Suggestions for advances in future climate change-recharge projections are given.
20. Pulido-Velazquez et al. (2015)	• A continuous balance model • RCM + delta method	Serral-Salinas aquifer, SE Spain	• Significant differences are obtained depending on the RCM; • Differences are also observed between the series with changes in means only and those also in standard deviations; • An increase in rainfall variability could increase recharge rates for a given mean rainfall; The ensemble of predictions estimates a reduction in mean annual recharge.
21. Touhami et al. (2015)	• HYDROBAL hydrological model; • 1 GCM (comparison with other 2)	South east Spain	• Climate change will have a significant impact on the soil water balance, especially on groundwater recharge; • Fewer rainfall events (>15mm) is projected, which promote aquifer recharge, longer dry summer seasons and, consequently, reduced average annual recharge.
22. Moeck et al. (2016)	• HydroGeoSphere • Future climate: ten GCM-RCM	Zürich Reckenholz lysimeter	• The choices in model structure and the consequence when simulating the recharge process are systematically evaluated; • The simpler model structures lead to differing recharge rates under extreme climate conditions; • Capturing climate extremes is critical when developing models; • Ensembles of climate projections should be coupled with ensembles of hydrogeological models
23. Hartmann et al. (2017)	• Two hydrological models: PCR-GLOBWB for the homogeneous subsurface and the karst recharge model VarKarst-R for the heterogeneous representation. • Future climate: Five GCMs	Europe, Northern Africa, and the Middle East	• Spatially variable storages and spatial concentration of recharge result in actual recharge rates that are up to four times larger for present homogeneous subsurface conditions and changes up to five times larger for potential future climate conditions than previously estimated under homogeneous subsurface properties.
24. This study	• Recharge from groundwater table fluctuation; • A wide range of climate statistics (38 rainfall, 12 temperature, and 21 evaporation) and non-climate variables (10 land and soil attributes, groundwater extraction, NDVI, and groundwater depth)	South Australia	• Seasonal rainfalls from May to September and April to October are more critical for groundwater recharge than annual rainfall; • A seasonal shift of rainfall could result in a decrease of recharge when the annual rainfall remains unchanged; • The mean groundwater depth has a statistically significant correlation with recharge spatially, which implies the caveats of current studies in the literature on the climate change impacts of groundwater recharge; • Nine out of ten soil/land attributes have a statistically significant correlation with recharge, and all of them have a statistically significant correlation with recharge percentage.

Table 2 Climate and non-climate parameters used in this study

Category	Variables	Parameters/statistics, abbreviations and units
Climate	Rainfall (38)	Annual rainfall (AP), mm
		Seasonal rainfall: Four seasons (MAM, JJA, SON, DJF) and May-Sep(M59)/Apr-Oct(M410) rainfall, mm
		Extreme rainfall: daily max (Dmax) and 99^{th}/95^{th} (P99/P95) daily rainfall, mm/day days over 99^{th}(D99)/95^{th}(D95) threshold, day rainfall on D99 (PD99)/D95(PD95), mm days over 99^{th}(D99W)/95^{th}(D95W) threshold on wet-day only, day rainfall on D99W (PD99W)/D95W(PD95W), mm
		Rainfall (>=1.0mm) days at annual (RD), May-Sep (RD59) and Apr-Oct(RD410) scales, day
		Rainfall intensity (AP/RD) at annual (RI), May-Sep (RI59) and Apr-Oct(RI410) scales, mm/day
		Annual rainfall above daily threshold of 5mm(R5), 10mm(R10), 20mm(R20), 30mm(R30), and 40mm(R40), mm
		Rainfall days above daily threshold of 5mm(RD5), 10mm(RD10), 20mm(RD20), 30mm(RD30), and 40mm(RD40), day
		Wet-Spell Length: mean (MeWS) and max (MxWS), day
		Dry-Spell Length: mean (MeDS) and max (MxDS), day
	Temperature (12)	Annual means of daily mean (Tmean), minimum (Tmin), maximum (Tmax) temperatures and diurnal temperature range (Tdiff), ^{o}C May-Sep and Apr-Oct means of above four variables, ^{o}C
	Evaporation (21)	Annual means of Class-A pan evaporation (Epan), FAO56 Penman-Monteith potential evapotranspiration (FAO56), Morton lake potential evaporation (Mlake), Morton potential evaporation (Mpot), Morton actual evaporation (Mpot), Morton wet evaporation (Mwet), and synthetic pan evaporation (Span). All with a unit of mm May-Sep and Apr-Oct means of above seven variables
Non-Climate	Land and soil attribute datasets (10)	Land system, available water holding capacity, depth to water table (category), land type, physical condition of soil, physical conditions of surface soil, recharge potential, soil group, soil subgroup and soil texture

	Groundwater extraction (GL)
	Time: Year
	Normalized difference vegetation index (NDVI)

Table 3 Stepwise regression results

	Groundwater Recharge	**Recharge Percentage**
Forward	Recharge ~ M410 + M59 + MxWS + MeWS + MactAnnual + GW.Extraction.GL + Year Multiple R-squared: 0.9077, Adjusted R-squared: 0.8892	Recharge/AP ~ M59 + MxWS + MeWS + GW.Extraction.GL + AP + SpanM410 + RI410 + FAO56M410 + MactAnnual Multiple R-squared: 0.8476, Adjusted R-squared: 0.8060
Backward	Recharge ~ M59 + M410 + RD410 + RI410 + MxWS + FAO56M410 + MactAnnual + SpanM410 + GW.Extraction.GL Multiple R-squared: 0.9190, Adjusted R-squared: 0.8969	Recharge/AP ~ M59 + M410 + RD410 + R5 + MxWS + FAO56M410 + MactAnnual + SpanM410 Multiple R-squared: 0.8450, Adjusted R-squared: 0.8085

Table 4 Correlation coefficients between groundwater recharge/percentage and soil/land attributes

Soil and Land Attributes	Recharge		Recharge Percentage		Category
	r	P-value	r	P-value	
Land System	0.72	0.0000	0.75	0.0000	70
Land Type	0.43	0.0000	0.50	0.0000	13
Soil Subgroup	0.45	0.0000	0.46	0.0000	32
Soil Texture	0.39	0.0000	0.41	0.0000	11
Depth to Water Table	0.37	0.0000	0.35	0.0000	9
Recharge Potential	0.33	0.0000	0.37	0.0000	9
Soil Group	0.33	0.0000	0.31	0.0002	15
Available Waterholding Capacity	0.22	0.0009	0.29	0.0000	6
Physical Condition of Soil	0.21	0.0037	0.23	0.0007	7
Physical Condition of Surface Soil	0.15	0.0560	0.26	0.0000	5

Highlights:

- Main controlling factors for groundwater recharge among 84 metrics were identified;
- Same annual rainfall with a seasonal shift could result in a decline of recharge;
- Lower groundwater depth could lead to a positive feedback of declining recharge;
- Spatially the most significant factors for recharge were soil and land attributes;
- Findings could serves as a reference for climate change impacts on groundwater.